A Container Truck Appointment Scheduling Problem Considering Hydrogen Refueling and Soft Time Windows

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Short summary

Rising maritime trade demand has exacerbated the challenges faced by drayage operators in inland container transportation. Drayage operators need to make precise truck scheduling decisions daily under truck appointments. Hydrogen-powered container trucks (HCTs) are promoted in container drayage, which brings further constraints for scheduling because of hydrogen refueling. A Mixed Integer Linear Programming (MILP) model for the container truck scheduling problem is proposed, which considers hydrogen refueling and soft time windows, aiming to minimize the total operational cost. To solve the proposed model, an improved Adaptive Large Neighborhood Search (ALNS) algorithm is designed, which is integrated with the Stochastic Local Search (SLS) and customized operators. Case studies demonstrate the effectiveness of the proposed model and algorithm. A novel perspective on container truck scheduling problems will be offered by the proposed model.
Keywords: Adaptive large-scale neighborhood search; Container truck appointment scheduling problem; Hydrogen refueling; Operations research applications; Soft time window

1 Introduction

Container drayage is a critical component of maritime logistics. As an approach of truck arrival management, truck appointment system (TAS) is considered as a solution to improve efficiency for drayage operators (Abdelmagid et al., 2022). Concurrently, environmental concerns are promoting the development of green means of transportation, such as hydrogen-powered container trucks (HCTs), for inland container drayage operations. However, the scheduling of HCTs in container drayage operations faces many challenges due to sparse refueling infrastructure (Camacho et al., 2022), strict truck appointment time windows, and the complexity of handling full and empty containers (Huang et al., 2024). Although traditional scheduling models such as the multi-Traveling Salesmen Problem with Time Window (m-TSPTW) have been applied (Chen et al., 2022), existing studies mainly focus on conventional diesel container trucks and lack consideration of refueling. Meanwhile, it has been observed that relaxing the restriction of time windows, can reduce operating costs and facilitate the management of operators dedicated to drayage, even including penalty costs (Escudero-Santana et al., 2021). The main contributions in this study will focus on:
(i)A Mixed Integer Linear Programming (MILP) model for container truck scheduling problem considering hydrogen refueling and soft time windows under truck appointments;
(ii)An improved Adaptive Large Neighborhood Search (ALNS) algorithm integrated with the Stochastic Local Search (SLS) and customized operators to efficiently solve the proposed model;
(iii)Numerical experiments verifying the effectiveness of the improved ALNS and the proposed model, while proving soft time windows are beneficial in reducing cost and providing managerial insights and decision support for new energy trucks scheduling in real-world drayage operations.

2 Methodology

Problem description

The study investigates a truck appointment scheduling problem considering hydrogen refueling and soft time windows, with container delivery and pickup tasks. Fig.1 shows the delivery and pickup tasks process. According to different types of the tasks (Huang et al., 2024), scheduled port

operation time, and hydrogen refueling requirements for HCTs, the drayage operators assign the tasks to a given number of HCTs, deciding the task sequence of each HCT. Within a scheduled port working time, the HCTs depart from the fleet depot, complete a sequence of tasks, and finally return to the fleet depot. In response to task requirements, the drayage operators need to assign the tasks through reasonable truck scheduling and ultimately achieve their business goals. The scheduling plans made by the drayage operators should minimize the total operating cost (Chen et al., 2022).

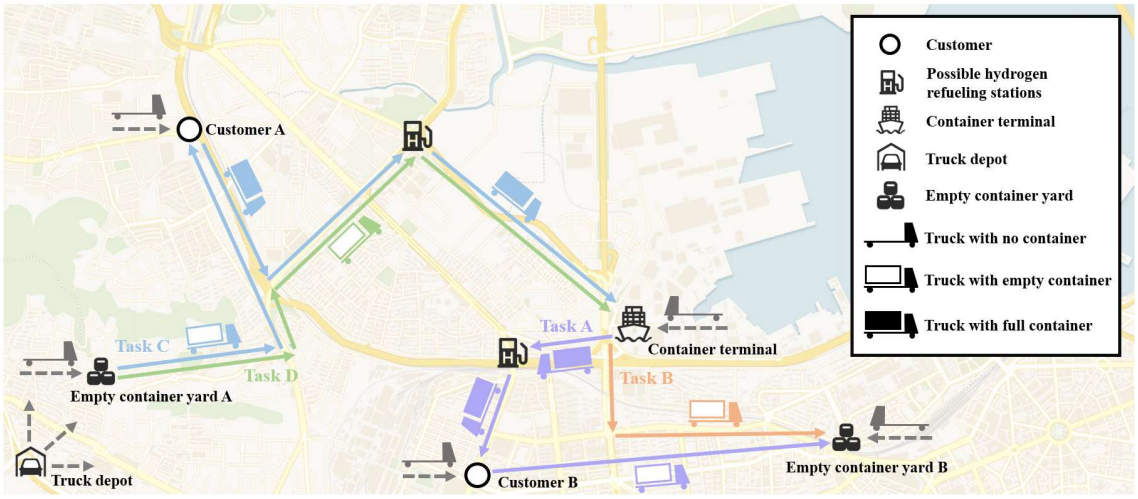


Figure 1: Delivery and pickup task scenario.

Truck appointment system sets several appointment time windows daily, each with upper limit for truck quotas. In practical situations, due to different traffic and working conditions inside and outside the port, it is quite possible that container trucks cannot arrive within the appointment time windows. Therefore, the container trucks may arrive in another time window. As shown in Fig.2, if the container trucks arrive earlier than the appointment time window, they should (i) wait until the appointment time window starts, or (ii) wait until the other time window opened by the port.

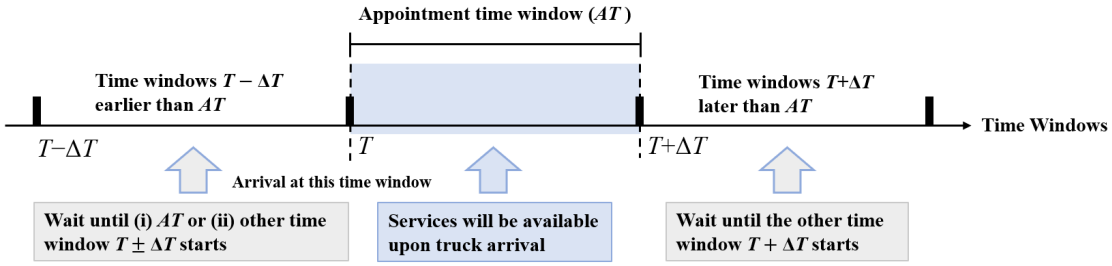


Figure 2: Time window adjustment.

Mathematical model

The notations used in the mathematical formulation are shown in Table 1. The optimization objective of the model is to minimize the total operational cost of HCTs throughout an operation, which comprises four components: the transportation cost of HCTs, the fixed cost of using HCTs, and the penalty cost for tasks not arriving within the scheduled time window, be denoted as z in Eq.(1). The proposed mathematical model is formulated as follows:

$$\min z = \alpha \sum_{(i,j)\in A} \sum_{m\in V} d_{ij} x_{ij}^m + \beta \sum_{j\in N\setminus\{o\}} \sum_{m\in V} x_{oj}^m + \gamma \sum_{\substack{i\in N\setminus N'_H \\ k=AT_i}} (1 - q_{ik}) \tag{1}$$

Eq.(2)-(7) represent the basic constraints of vehicle scheduling problem:

$$s.t. \sum_{j\in N\cup\{d\}} \sum_{m\in V} x_{ij}^m = 1, \forall i \in N \setminus N'_H \tag{2}$$

Table 1: Notations and definitions.

Notation	Definition
Set	
N	Set of all tasks, N=$N_1 \cup N_2 \cup N'_H$
N_1/N_2	Set of container pickup/delivery tasks, $N_1, N_2 \in N$
N_H	Set of hydrogen refuelling tasks
N'_H	Set of virtual nodes which allowing repeated visits to the hydrogenation tasks in the set N_H, $N'_H \in N$
N'_h	Set of virtual nodes corresponding to the physical hydrogen refueling station, $h \in N_H$, $N'_h \subseteq N'_H$
A	Set of all task arcs
o/d	Origin/destination of truck depot
K	Set of appointment time slot, K=1,2,. . . ,12
V	Set of HCTs, V=1,2,. . . ,V_m
i, j	Index of tasks, $i, j \in N \cup \{o, d\}, (i, j) \in A$
Parameters	
$h(i)$	Physical hydrogen refueling station to which the virtual node $i \in N'_H$ belongs, $h(i) \in N_H$
α, β, γ	Weight coefficients of travel cost, fixed cost and penalty cost
AT_i	Appointment time window for task i, $AT_i \in K$
$[e_{ik}, l_{ik}]$	Time window for task i in the kth time period
WT_i	Waiting time for task i
d_{ij}	Travel distance between task i and task j
d_i	Travel distance in task i
v	Speed of HCTs
$P^{\text{in}}, P^{\text{out}}$	Maximum container delivery/pickup capacity at port
H	Maximum hydrogen capacity of a HCT
μ	Hydrogen consumption per unit distance traveled by a HCT
M	A sufficiently large constant
Variables	
x_{ij}^m	Binary variable, 1 if task i is completed by HCT m and then proceeds to execute task j
q_{ik}	Binary variable, 1 if time window k is selected by task i
s_i	Start time of task i
h_i^m	Remaining energy when HCT m starts task i

$$\sum_{j \in N \cup \{d\}} \sum_{m \in V} x_{ij}^m \leq 1, \forall i \in N'_H \tag{3}$$

$$\sum_{j \in N} x_{oj}^m \leq 1, \forall m \in V \tag{4}$$

$$\sum_{m \in V} x_{ij}^m = 0, \forall i, j \in N'_h, \forall h \in H, i \neq j \tag{5}$$

$$\sum_{j \in N \cup \{d\} \setminus \{i\}} x_{ij}^m = \sum_{j \in N \cup \{o\} \setminus \{i\}} x_{ji}^m, \forall i \in N \setminus N'_H, \forall m \in V \tag{6}$$

$$\sum_{j \in N \cup \{d\} \setminus \{i\}} x_{ij}^m = \sum_{j \in N \cup \{o\} \setminus \{i\}} x_{ji}^m, \forall i \in N'_H, \forall m \in V \tag{7}$$

Eq.(8)-(11) ensure the continuity of access time for adjacent tasks and are related to soft time windows:

$$s_j \geq s_i + WT_i + \frac{d_{ij} + d_i}{v} - M(1 - x_{ij}^m), \forall i \in N \cup \{o\} \setminus N'_H, \forall j \in N \cup \{d\}, \forall m \in V, i \neq j \tag{8}$$

$$s_j \geq s_i + \frac{d_{ij} + d_i}{v} - M(1 - x_{ij}^m), \forall i \in N'_H, \forall j \in N \cup \{d\}, \forall m \in V, i \neq j \tag{9}$$

$$e_{ik} - M(1 - q_{ik}) \leq s_i \leq l_{ik} + M(1 - q_{ik}), \forall k \in K, \forall i \in N_1 \tag{10}$$

$$e_{ik} - M(1 - q_{ik}) \leq s_i + d_i/v - WT_i \leq l_{ik} + M(1 - q_{ik}), \forall k \in K, \forall i \in N_2 \tag{11}$$

Eq.(12)-(14) control the allocation of tasks:

$$\sum_{k=1}^{12} q_{ik} = 1, \forall i \in N \setminus N'_H \tag{12}$$

$$\sum_{i \in N_2} q_{ik} \leq P^{\text{in}}, \forall k \in K \tag{13}$$

$$\sum_{i \in N_1} q_{ik} \leq P^{\text{out}}, \forall k \in K \tag{14}$$

Eq.(15)-(17) represents the energy consumption of HCTs:

$$0 \leq h_i^m \leq H, \forall i \in N \cup \{o, d\}, \forall m \in V \tag{15}$$

$$h_j^m \leq h_i^m - \mu(d_{ij} + d_i) + M(1 - x_{ij}^m), \forall i \in N \setminus N'_H, \forall j \in N \cup \{d\}, \forall m \in V, i \neq j \tag{16}$$

$$h_j^m \leq H - \mu \cdot d_{ij} + M(1 - x_{ij}^m), \forall i \in N'_H \cup \{o\}, \forall j \in N \cup \{d\}, \forall m \in V, i \neq j \tag{17}$$

The range of values for decision variables is limited as shown in constraints (18)-(20):

$$x_{ij}^m, y_i, q_{ik} \in \{0, 1\}, \forall i, j \in N \cup \{o, d\}, \forall m \in V, \forall k \in K \tag{18}$$

$$s_i \in N^+, \forall i \in N \cup \{o, d\} \tag{19}$$

$$h_i^m \geq 0, \forall i \in N \cup \{o, d\}, \forall m \in V \tag{20}$$

Solution Algorithm

Among various heuristic algorithms, The ALNS has been successfully applied to variants of the VRP (Voigt, 2025), achieving good results when considering time windows, making it suitable for solving the proposed model. Inspired by Jiang et al. (2025) and Sun et al. (2025), several operators and local search procedures are improved of the ALNS solve the proposed model. The solution is presented as a task service sequence of a HCT. Each sequence consists of depots and visited tasks, indicating the service order of tasks. The refueling and time window constraints are considered in designing the removal and insertion operators. Based on the characteristics of the model, four removal operators and five insertion operators are designed. Removal operators include directional removals (worst energy removal, worst time removal, longest distance removal) and random removal. Insertion operators include greedy insertion and its improved versions, regret insertion, clustering insertion, and time constraint insertion. A stochastic local search algorithm is used to optimize the service start time of each node in the evaluation function avoiding local optimal solution caused by the time relaxation of soft time windows. Simulated annealing criteria is used to determine whether the obtained new solution is accepted. Roulette wheel method is used to select removal and insertion operators during the iteration process.

3 Results and discussion

In case studies, instances of different scales are randomly generated based on real-world operation scenarios and key industry research literature (Escudero-Santana et al., 2021; Camacho et al., 2022; Cui et al., 2022; Huang et al., 2024). Instance sizes range from a minimum of 8 tasks to a maximum of 200 tasks. The numerical experiments consist of 30 instances, including 15 small-scale instances and 15 medium and large-scale instances. We categorize the instances using the nomenclature T_H_C_n, where T, H, and C represent the number of tasks, hydrogen refueling stations, and available container trucks, respectively, and n indicates the specific dataset index within that category.

The results of small-scale instances are summarized in Table 2. Columns 4 and 5 report the minimum objective value and computation time obtained by CPLEX. Columns 6 and 7 display the solution results and computation times for the IALNS. The final Gap% column refers to the deviation between CPLEX and IALNS solutions, calculated by $Gap\% = (Total\ Cost_{IALNS} - Total\ Cost_{CPLEX})/Total\ Cost_{CPLEX} \times 100$. Negative Gap% values affirm that the improved ALNS outperforms CPLEX in solution quality.

Table 2: Experiments of small-scale instances.

No.	T_H_C_n	CPLEX		improved ALNS		Gap%
		Total Cost	Runtime(s)	Total Cost	Runtime(s)	
1	8_1_2_1	222.00	2.35	222.00	0.04	0.00
2	8_1_2_2	271.50	2.08	271.50	0.05	0.00
3	8_1_2_3	227.50	1.15	227.50	0.04	0.00
4	10_1_2_1	249.50	5.28	249.50	0.23	0.00
5	10_1_2_2	256.00	9.96	256.00	0.23	0.00
6	10_1_2_3	244.00	5.56	244.00	0.22	0.00
7	12_1_2_1	267.00	78.70	267.00	0.27	0.00
8	12_1_2_2	252.50	34.09	252.50	0.26	0.00
9	12_1_2_3	277.00	85.94	277.00	0.28	0.00
10	14_1_3_1	301.50	3600.00	303.00	3.07	0.50
11	14_1_3_2	298.00	3600.00	299.00	3.17	0.34
12	14_1_3_3	289.50	400.77	292.00	3.27	0.86
13	16_1_3_1	297.50	3600.00	298.50	6.48	0.34
14	16_1_3_2	338.00	3600.00	316.00	5.92	-6.51
15	16_1_3_3	336.00	3600.00	316.00	6.20	-5.95

For instances 1-9, CPLEX successfully identified the optimal solutions. However, for instances 10, 11 and 13–15, CPLEX failed to obtain the global optimum within 3600s. For small-scale instances, the total cost obtained by the improved ALNS is almost identical to the total cost from CPLEX and even outperforms CPLEX in instances 10, 11, and 13–15. The results demonstrate that the improved ALNS performs well on small-scale instances. The computing time of the improved ALNS is reduced to within 10s, outperforming CPLEX in solution efficiency.

GA+SLS and the improved ALNS are applied to solve medium and large-scale instances. The results are summarized in Table 3. Columns 3-6 present the objective values and computation times for the GA+SLS and the improved, respectively. Columns 9-10 detail the percentage deviations in total cost and runtime. Gap1% column refers to the deviation of total cost between the GA+SLS and the improved ALNS, calculated by $Gap1\% = (Total\ Cost_{IALNS} - Total\ Cost_{GA+SLS})/Total\ Cost_{GA+SLS} \times 100$. Gap2% column calculates the deviation of algorithm runtime between GA+SLS and the improved ALNS by $Gap2\% = (Runtime_{IALNS} - Runtime_{GA+SLS})/Runtime_{GA+SLS} \times 100$. Negative Gap1 and Gap2 values affirm that the improved ALNS outperforms GA+SLS in both solution quality and efficiency.

For instances 16-30, the improved ALNS reduces total costs by an average of 9.45% compared to GA+SLS, demonstrating its superior performance. Regarding computation time, the improved ALNS is consistently faster, reducing total runtime by an average of 5.52% compared to the GA+SLS. Meanwhile, results from some medium and large-scale instances show that a reduction in the number of hydrogen refueling stations leads to an increase in operating costs. With fewer

Table 3: Experiments of medium and large-scale instances.

No.	T_H_C_n	GA+SLS		improved ALNS		Gap1%	Gap2%
		Total Cost	Runtime(s)	Total Cost	Runtime(s)		
16	80_3_18	2077.50	105.97	1758.50	91.35	-15.35	-2.95
17	90_2_20	2225.00	108.14	1884.50	107.98	-15.30	-7.87
18	90_3_20	2169.00	123.48	1954.00	117.33	-9.91	-4.59
19	100_2_30	2500.50	133.95	2206.00	124.50	-11.78	-5.30
20	100_3_30	2506.50	109.09	2107.50	105.38	-15.92	-11.26
21	120_2_32	3117.50	211.59	2880.50	181.59	-7.60	-3.31
22	120_3_32	3027.00	196.89	2862.00	182.88	-5.45	-10.87
23	140_2_34	3692.50	246.52	3121.50	229.74	-15.46	-4.40
24	140_3_34	3826.00	243.34	3693.00	240.42	-3.48	-5.56
25	160_2_36	4231.50	256.52	4223.50	254.78	-0.19	-1.07
26	160_3_36	4380.00	260.09	3984.50	236.35	-9.03	-1.26
27	180_2_38	5058.50	322.95	4818.00	304.40	-4.75	-3.65
28	180_3_38	4880.50	331.00	4514.50	322.86	-7.50	-5.68
29	200_2_40	5665.50	385.38	5015.50	328.64	-11.47	-9.23
30	200_3_40	5640.00	371.62	5154.00	321.71	-8.62	-5.85
Average						**-9.45**	**-5.52**

refueling stations available, container trucks must detour to more distant stations to refuel, resulting in higher detour costs. In summary, the IALNS demonstrates significant advantages in both solution quality and computational efficiency.

Scholars are focusing on the application of soft time windows (Escudero-Santana et al., 2021; Gala et al., 2022), which has gained significance. Nine small-scale instances are selected to compare the operational cost differences between soft and hard time windows. Table 4 displays the results between soft time window and hard time window. Gap% column refers to the cost variance between soft time window and hard time window, calculated by using the formula $Gap\% = (Total\ Cost_{soft\ time\ window} - Total\ Cost_{hard\ time\ window})/Total\ Cost_{hard\ time\ window} \times 100$. Negative Gap values indicate that the soft time window solution is more cost-effective. The results demonstrate the improved ALNS effectively solves the proposed model with soft time window constraints, resulting in a lower total cost. By imposing reasonable penalty costs, soft time windows allow container trucks to arrive at the port with permissible deviations from the appointment time windows. Soft time windows can provide more flexible scheduling alternatives for truck scheduling, which can lead to more optimal solution. In further research, numerical experiments with varying numbers of hydrogen refueling stations will be designed to reveal the impact of station density on operational costs.

Table 4: Results between Soft Time Window and Hard Time Window.

T_H_C	Hard Time Window	Soft Time Window	Gap%
8_1_2_2	314.50	271.50	-13.67
8_1_2_3	251.00	227.50	-9.36
8_1_2_4	243.00	241.50	-0.62
10_1_2_1	268.00	249.50	-6.90
10_1_2_2	286.00	256.00	-10.49
10_1_2_3	274.50	244.00	-11.11
12_1_2_4	270.00	248.50	-7.96
12_1_2_5	278.00	266.00	-4.32
12_1_2_6	288.00	279.00	-3.13
Average			**-7.51**

4 Conclusions

A container truck appointment scheduling problem is introduced, considering hydrogen refueling and soft time windows, with the objective of minimizing total operational costs, which include travel costs, fixed truck expenses, and time penalties. A mixed integer linear programming model is formulated to describe the container truck appointment scheduling problem. The proposed model is solved efficiently by an ALNS algorithm, which is improved by designing customized operators and the SLS algorithm. The validity of the proposed model and algorithm is confirmed through comparisons with CPLEX on small-scale instances and through superior performance on medium and large-scale instances over general genetic algorithm. The use of soft time windows can reduce operational costs compared with hard time windows. A novel perspective will be offered by considering soft time windows and hydrogen refueling when studying container truck appointment scheduling problems. The proposed model can provide effective solutions for operators to optimize truck scheduling and reduce operational costs in practical container drayage.

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